Multi-Target Tracking for High Frequency Active Systems

Christian G. Hempel, Ph.D.
Sensors and Sonar Systems Department, Code 1522
Naval Undersea Warfare Center
1176 Howell Street
Newport, RI 02841
phone: (401) 832-8648 fax: (401) 832-2757 email: hempelcg@npt.nuwc.navy.mil

Mr. Stephen G. Greineder
Sensors and Sonar Systems Department, Code 159B
Naval Undersea Warfare Center
1176 Howell Street
Newport, RI 02841
phone: (401) 832-8238 fax: (401) 832-2757 email: greinedersg@npt.nuwc.navy.mil

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OBJECTIVES

The purpose of the effort reported here is to investigate modern multi-target tracking algorithms for high frequency active applications. High frequency active sensor systems are currently being evaluated by the Navy to meet the Sea Power 21 Sea Shield objectives for force protection and port security. These systems have elementary baseline tracking capabilities and could benefit from incorporating an advanced acoustic multi-target tracking algorithm designed for distributed active sensors. The incorporation of an improved tracking capability is aimed at reducing the high rate of false tracks being reported during system testing. This effort used active measurements from prototype actve sonar sensors to demonstrate true multi-target tracking on structured test data provided by ARL/UT, assess overall tracking performance and identify areas requiring algorithm improvements.

APPROACH

The limited overall scope of this investigation required focusing on a single tracking method that was likely to demonstrate improvement over an existing baseline tracker. Several different tracking methods were considered for this study: Bayesian (e.g., particle filter), recursive (e.g., Kalman filter), and batch methods (e.g., Multi-Hypothesis Tracking and Probabilistic Multi-Hypothesis Tracking). The prototype active sonar system and associated baseline processing chain considered in this study is capable of producing high resolution target detections at a high rate relative to the expected target dynamics. Consequently, Bayesian methods were not investigated because they are best suited to applications involving highly non-linear or non-Gaussian state or process equations. Moreover, the baseline tracker is recursive and hence batch type tracking methods were made the focus of this study. Multi-Hypothesis Tracking (MHT) is a batch type tracking method that, under ideal conditions, enumerates all possible data association hypotheses and produces maximum likelihood estimates of the target track. For situations containing a significant amount of clutter or false detections the computational burden of MHT may require limiting the number of data association hypotheses. This modification makes the algorithm and implementation much more complicated and sacrifices any

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optimality properties. Some probabilistic data association methods can handle significant amounts of clutter without enumerating a large number of data association hypotheses. The Probabilistic Multi-Hypothesis Tracking (PMHT) algorithm developed by Streit and Luginbuhl [1] is a batch technique that uses the Expectation-Maximization (EM) algorithm to obtain MAP estimates of the sequence of target states. The application considered here often produces a large amount of clutter and PMHT has been successfully demonstrated by one of the authors on other active sonar data containing clutter [16]. Therefore, the technical approach that guided this effort was to leverage NUWC's expertise in the PMHT algorithm and apply an existing implementation (with appropriate modifications) to the data provided by ARL/UT.

PMHT is based on the assumption there are M independent targets with states that evolve in discrete time according to equation (1):

$$\mathbf{x}_m(t+1) = \mathbf{F}_m(t)\mathbf{x}_m(t) + \mathbf{G}_m(t)\mathbf{u}_m(t) + \mathbf{v}_m(t) \qquad 1)$$

for $m = 1,2,\ldots,$M. The matrices $\mathbf{F}_m(t)$ and $\mathbf{G}_m(t)$, and the input $\mathbf{u}_m(t)$ are known, and $\mathbf{v}_m(t)$ is assumed to be zero-mean, Gaussian white noise with covariance matrix given by $\mathbf{Q}_m(t)$. In practice, the control inputs, $\mathbf{u}_m(t)$, are assumed to be known and are typically used to account for platform motion changes. However, for ease of presentation, it is assumed, without loss of generality, that $\mathbf{u}_m(t)$ is zero.

The measurement equation for target m is given by equation (2).

$$\mathbf{z}_m(t) = \mathbf{H}_m(t)\,\mathbf{x}_m(t) + \mathbf{w}_m(t)\,, \qquad 2)$$

where the measurement noise, $\mathbf{w}_m(t)$, is additive, zero-mean, Gaussian white noise with known covariance matrix $\mathbf{R}_m(t)$. In practice, some active transmissions provide an estimate of contact Doppler as well as position. Since the Doppler component of such a measurement is a nonlinear function of $\mathbf{x}_m(t)$, it is assumed here that a suitable linear approximation (i.e., first-order Taylor series expansion) can be computed as needed.

The derivation of PMHT requires several additional independence assumptions. First, measurements within a scan of data, $\mathbf{Z}(t) = \{\mathbf{z}_r(t)\}_{r=1}^{N_t}$, are independent and identically distributed when they are conditioned on the target states, $\mathbf{X}(t) = \{\mathbf{x}_m(t)\}_{m=1}^{M}$. In the active sonar application presented here, these measurements are in the form of clusters. Also, measurements in different scans are independent, conditioned on the target states. The measurement-to-target assignments, denoted by $\mathbf{K}(t) = \{k_r(t)\}_{r=1}^{N_t}$, are assumed independent from measurement to measurement, between time scans, and from the target states. The mixture proportions (i.e., the fraction of measurements assigned to target m at scan t) are denoted by $\pi_m(t)$. PMHT is a batch algorithm: so let T be the batch length, and define $\mathbf{Z} = \{\mathbf{Z}(t)\}_{t=1}^{T}$, $\mathbf{X} = \{\mathbf{X}(t)\}_{t=1}^{T}$, and $\mathbf{K} = \{\mathbf{K}(t)\}_{t=1}^{T}$ for notational convenience. Under these assumptions, the joint probability density function of $\mathbf{Z}$, $\mathbf{X}$, and $\mathbf{K}$ is given by equations (3) and (4).

$$P(\mathbf{Z},\mathbf{X},\mathbf{K})=\left\{\prod_{\nu=1}^{M} N\left(\mathbf{x}_\nu(0);\bar{\mathbf{x}}_\nu(0),\mathbf{P}_\nu(0)\right)\right\}$$
$$\times\prod_{t=1}^{T}\left\{\left[\prod_{s=1}^{M} N\left(\mathbf{x}_s(t);\mathbf{F}_S(t)\mathbf{x}_s(t-1),\mathbf{Q}_s(t)\right)\right]\left[\prod_{r=1}^{n_t}\left[\pi_{tm}\left[N\left(\mathbf{z}_{tr}(t);\mathbf{H}_m(t)\mathbf{x}_m(t),\mathbf{R}_m(t)\right)\right]\Big|_{m=k_{tr}}\right]\right]\right\}, \tag{3}$$

and

$$P(\mathbf{Z},\mathbf{X})=\sum_K P(\mathbf{Z},\mathbf{X},\mathbf{K})=\left\{\prod_{\nu=1}^{M} N\left(\mathbf{x}_\nu(0);\bar{\mathbf{x}}_\nu(0),\mathbf{P}_\nu(0)\right)\right\}$$
$$\times\prod_{t=1}^{T}\left\{\left[\prod_{s=1}^{M} N\left(\mathbf{x}_s(t);\mathbf{F}_S(t)\mathbf{x}_s(t-1),\mathbf{Q}_s(t)\right)\right]\left[\prod_{r=1}^{n_t}\left[\sum_{m=1}^{M}\pi_{tm}\left[N\left(\mathbf{z}_{tr}(t);\mathbf{H}_m(t)\mathbf{x}_m(t),\mathbf{R}_m(t)\right)\right]\right]\right]\right\}. \tag{4}$$

PMHT is a variant of the iterative EM algorithm [4], [5], [6]. PMHT, like EM, is characterized by an E-step and an M-step. In the E-step, the objective function for the current iteration is formed by computing the expectation (with respect to **K**), conditioned on the data and the previous estimate, as given in equation (5):

$$\begin{aligned}Q(\mathbf{X}^{n+1},\mathbf{X}^{n}) &= E\left[\log\{P(\mathbf{Z},\mathbf{X}^{n+1},\mathbf{K})\}\Big|\mathbf{Z},\mathbf{X}^{n}\right]\\ &=\sum_K \log\{P(\mathbf{Z},\mathbf{X}^{n+1},\mathbf{K})\}\mathrm{K}(\mathbf{K}\mid\mathbf{Z},\mathbf{X}^{n})\\ &=\sum_K \log\{P(\mathbf{Z},\mathbf{X}^{n+1},\mathbf{K})\}\left[\frac{P(\mathbf{Z},\mathbf{X}^{n},\mathbf{K})}{P(\mathbf{Z},\mathbf{X}^{n})}\right],\end{aligned} \quad 5)$$

where the superscripts refer to the iteration. This effectively marginalizes out the unknown assignments. Substituting in equations (3) and (4) and rearranging terms yields

$$Q(X^{n+1},X^{n})=\sum_{t=1}^{T}\sum_{r=1}^{N_t}\sum_{m=1}^{M} w_{mr}^{n}(t)\log\pi_m^{n+1}(t)+\sum_{m=1}^{M}\log(N(\mathbf{x}_m^{n+1}(0);\overline{\mathbf{x}_m},\bar{\mathbf{P}}_m))$$
$$+\sum_{m=1}^{M}\sum_{t=1}^{T}\left\{\begin{array}{l}\log(N(\mathbf{x}_m^{n+1}(t);\mathbf{F}_m(t)\mathbf{x}_m^{n+1}(t-1),\mathbf{Q}_m(t-1)))\\ +\sum_{r=1}^{N_t} w_{mr}^{n}(t)\log(N(\mathbf{z}_r(t);\mathbf{H}_m(t)\mathbf{x}_m^{n+1}(t),\mathbf{R}_m(t)))\end{array}\right\}, \quad 6)$$

with the assignment weights, $w_{mr}^{n}(t)=\Pr\{k_r(t)=m\mid\mathbf{Z},\mathbf{X}^{\mathrm{n}}\}$, given by

$$w_{mr}^n(t) = \frac{\pi_m(t) N(\mathbf{z}_r(t); \mathbf{H}_m(t)\mathbf{x}_m^n(t), R_m(t))}{\sum_{s=1}^{M} \pi_s(t) N(\mathbf{z}_r(t); \mathbf{H}_s(t)\mathbf{x}_s^n(t), R_s(t))}, \qquad 7)$$

so that
$$\mathrm{K}(\mathbf{K} \mid \mathbf{Z}, \mathbf{X}^n) = \prod_{t=1}^{T} \prod_{r=1}^{N_t} w_{mr}^n(t)\Big|_{m=k_r(t)} .$$

The M-step is a maximization of $Q(\mathbf{X}^{n+1}, \mathbf{X}^n)$ over $\mathbf{X}^{n+1}$ to achieve the MAP estimate of the target states. Streit and Luginbuhl [1] observe that the part of $Q(\mathbf{X}^{n+1}, \mathbf{X}^n)$ depending on $\mathbf{X}^{n+1}$ is really just the natural logarithm of the probability density function of a bank of independent Kalman filters, so that the solution is attained from a fixed-interval Kalman smoother. The "synthetic measurements" used in the Kalman smoother are the centroids:

$$\tilde{\mathbf{z}}_m^n(t) = \frac{\sum_{r=1}^{N_t} w_{mr}^n(t)\mathbf{z}_r(t)}{\sum_{r=1}^{N_t} w_{mr}^n(t)}, \qquad 8)$$

with corresponding synthetic covariance matrices given by

$$\tilde{\mathbf{R}}_m^n(t) = \frac{\mathbf{R}_m(t)}{\sum_{r=1}^{N_t} w_{mr}^n(t)} . \qquad 9)$$

Ideally, the EM steps are iterated until a suitable convergence criterion is satisfied. In practice, however, a fixed number of iterations (e.g., 5 to 10) is usually adequate [2].

Active sonar applications require the ability to track targets in highly cluttered environments. The Probabilistic Multi-Hypothesis Tracking for Active Sonar (PMHTAS) algorithm employs a spurious target model to represent clutter, following the method of Willett, Ruan, and Streit [8]. The clutter is assumed to be distributed uniformly in space having volume V, the number of clutter measurements given by a Poisson distribution with parameter λ. The clutter density parameter, λ, is estimated adaptively for each track by looking at data in a large region encompassing the predicted target state. In the single target case, two possibilities for the origin of a measurement are modeled: clutter appears with probability π_0 and target with probability π_1. These probabilities are computed from the posterior probability conditioned on the number of measurements:

$$\pi_1 = \frac{P_d}{P_d N_t + (1 - P_d)\lambda V},$$
$$\pi_0 = 1 - \pi_1, \qquad 10)$$

where P_d is the sensor probability of detection. The PMHT weights from equation (7) are now given by equation (11), with the measurement matrix **H** replaced by a function h(t,x), which may be nonlinear:

$$w_{1r}^{n}(t)=\frac{\pi_1(t)N(z_r(t);h_1(t,x_1^n(t)),R_1(t))}{\frac{\pi_0(t)}{V}+\pi_1(t)N(z_r(t);h_1(t,x_1^n(t)),R_1(t))}. \qquad 11)$$

Figure 1 is a flow diagram for one update cycle of PMHTAS and provides a brief overview of the algorithm.

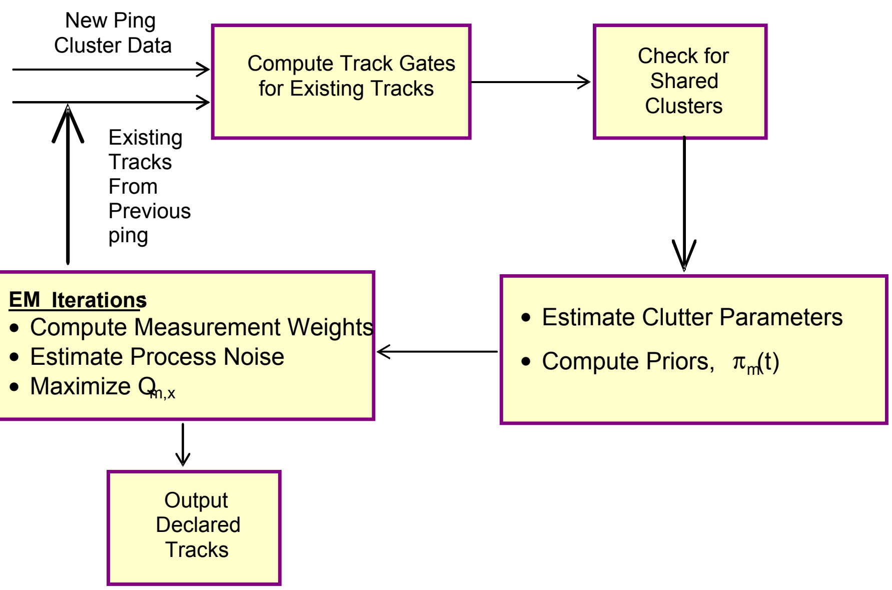

Figure 1. Processing flow diagram.

At each update, new data received from the clustering algorithm are used to update existing tracks. Gating is not required since PMHT is a true multi-target tracking algorithm. However, it is practical to avoid performing many floating point operations with zero weights. PMHTAS is an environmentally adaptive algorithm in that parameters from the spatial probability density functions are estimated from the data.

FY06 WORK COMPLETED

Task 1: Obtained available structured and reconstructed test data collected on relevant prototype active sensors from ARL/UT.

Task 2: Investigated and selected appropriate active sonar multi-target target tracking algorithm.

Task 3: Prototyped candidate tracking algorithm in MATLAB. Modified data association stage and models of target dynamics as needed.

Task 4: Demonstrated performance of algorithm prototype on sea trial data.

RESULTS AND CONCLUSIONS

A set of 14 structured test runs collected on a prototype monostatic system was provided by ARL/UT to evaluate the tracking performance of a Matlab implementation of PMHTAS. The data sets consist of multiple runs differing in the contact type (surface/sub-surface). For the subsurface contacts there were two different configurations of the contact. Each data set consists of, among other information, range, bearing, and amplitude clusters representing both targets, interference and clutter (returns due to random background noise, returns from stationary objects, etc.). For each run, the range and bearing clusters were converted to Cartesian coordinates to match the assumptions of our existing PMHTAS algorithm. The biases that result from this transformation were not considered to be significant sources of error for this tracking problem. In all cases PMHTAS tracks of batch length 10 pings were manually initialized on the Cartesian cluster data based on information on target position in the data logs. The leading edge, or "head," of the batch for each target represents the track estimate at the current ping, that is, the filtered estimate for the track; the trailing edge, or "tail," of the batch for each track represents the smoothed estimate for the track, with a lag of 10 pings. At each ping, the new clusters are added to the head of the batch for each track, and the oldest clusters in the batch are removed from the tail of the batch before updating the tracks. In this fashion, the 10 ping batch of data for each track is slid forward in time one ping at a time. Using a batch of data to update the track estimates greatly improves the cluster-to-track association process for multi-target tracking.

Contact insertion point information and run plans for the contacts were provided in the data logs, but complete ground truth information about the actual trajectories of the contacts was not available. Thus, in this report, observations on tracking performance are largely qualitative. Based on the insertion point information, each of the geographic plots shown below is zoomed into the relevant region of interest having the sensor always located at the origin.

Figures 2 through 14 illustrate the tracking performance of the baseline and PMHTAS trackers on the data sets. Each plots shows the accumulated clusters in the region of interest over many pings, where each cluster is plotted with intensity commensurate with its amplitude. While a true appreciation for this tracking problem can only be obtained by observing the clusters as they arrive from one ping to the next, these summary plots are adequate for the present discussion. In each of these plots, the baseline tracker (which is only reported every 5 pings) is plotted with circles, the "head" of the PMHTAS tracker is plotted with dots, and the "tail" of the PMHTAS tracker is plotted with solid lines.

Figures 2 through 5 show the tracking performance of the baseline and PMHTAS trackers on the four data sets for the first configuration of the sub-surface contact. In all cases the tracking performance of the baseline and PMHTAS trackers are nearly identical. Clearly these runs are characterized by light clutter and high signal-to-noise ratio (SNR). Consequently, neither the baseline nor the PMHTAS algorithms have difficulty tracking the target.

Figures 6 through 10 show the performance of the baseline and PMHTAS trackers on the five data sets with the contact in configuration 2. These runs are characterized by light to heavy clutter, low to high SNR, and are clearly more challenging. PMHTAS outperforms the baseline tracker on 5 contacts in runs 2, 5, 13, and 14 (figures 6, 7, 9, and 10). While some of the performance gain by PMHTAS may be due to the manual initialization (e.g., the left target in run 13, figure 9), there are some contacts that the baseline tracker does not track and that are visually evident in the cluster data (e.g., the right target in run 5, figure 7). The baseline tracker, however, outperformed PMHTAS on two targets in runs 10 and 13 (figures 8 and 9). It must be noted that the target in run 10 (figure 8) is not visually evident in the detection data and without ground truth it is impossible to verify that the baseline tracker successfully tracked the target in that data set. When the baseline tracker outperformed PMHTAS the level of cutter is very high and therefore these results are not surprising because the implementation of PMHTAS used in this analysis did not utilize amplitude or any other classification feature to improve data association. Comparable tracking performance was observed on two targets in runs 2 and 13 (figures 6 and 9). Overall, PMHTAS provided moderately better tracking performance on the second configuration of the sub-surface contact but more work needs to be done to achieve the desired tracking performance in the presence of heavy clutter.

Data was also supplied for four surface contact runs, shown here in figures 11 through 14. PMHTAS significantly outperformed the baseline tracker on two of the contacts in runs 5 and 13a (figures 12 and 14, respectively). Comparable tracking performance was observed on the remaining surface contacts.

From these results it is reasonable to conclude that both methods are capable of tracking subsurface contacts with the first configuration to an acceptable level of performance. Moreover, PMHTAS may be capable of significantly better performance than the baseline tracker on both the second configuration of the subsurface contact and the surface contact. It must be emphasized that a fair comparison of the PMHTAS and baseline tracking algorithms requires full automation of the PMHTAS algorithm. There is ongoing research and development at NUWCDIVNPT of a track maintenance function for PMHTAS and further application of PMHTAS to the high frequency active problem should include these algorithm developments. Furthermore, a thorough quantitative comparison of the two tracking algorithms requires more complete truth and reconstruction information. This information is clearly required to compute standard statistics like mean-square error and bias, but perhaps more importantly for the anticipated application of interest, it is also necessary for computing standard tracking metrics such as time-to-detect, hold-time, track break-up, and percent correctness.

SUMMARY AND RECCOMMENDATIONS

In addition to the issues regarding track maintenance and reconstruction information discussed above, more effort is clearly needed to develop models of target and non-target echo amplitude (or some other appropriate classification feature) to improve data association in PMHTAS. In the data analyzed here all of the runs where PMHTAS performed poorly have significant levels of clutter. It appears that the poor performance of the PMHTAS algorithm in those cases is primarily attributable to the absence of models for cluster amplitude. Any further application of the PMHTAS algorithm, or any other multi-target tracking algorithm, to the high frequency active tracking problem should use some appropriate classification feature. Classification feature information may also improve the track maintenance functions. These and other recommended system and tracking related improvements are summarized in the list below.

- Incorporate automated track maintenance functions into PMHTAS

- Develop and incorporate appropriate classification feature models (e.g., amplitude or highlight structure) into PMHTAS.

- Develop maps of the persistent clutter and use them to reduce false detections passed to the tracking function.

- Utilize Doppler sensitive waveforms in specific applications.

- Include thorough truth and reconstruction information in all future data driven analyses.

RELATED PROJECTS

- There is a related effort being conducted at NRL to develop a physical understanding of the expected high frequency returns from the contacts used in this investigation. This information could form the basis for robust classification and be directly inserted into the tracker measurement stage to eliminate clutter measurements.

- There is an ongoing effort funded by PMS 480 to understand the present capabilities of proposed automated high frequency active tracking systems. Advances from this effort could be applicable to issues identified by the current effort.

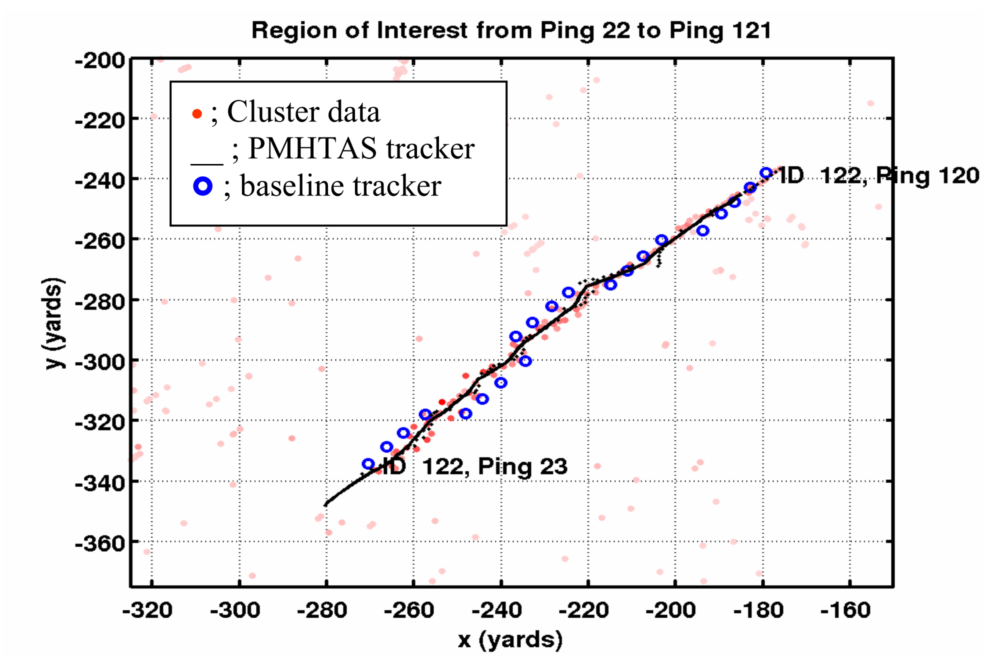

Figure 2. Subsurface Contact (configuration 1) run 2. Cluster data is show in red, baseline tracker output is shown in blue and PMHTDAS track output is shown in black. Tracking performance is nearly identical for both systems on this data set.

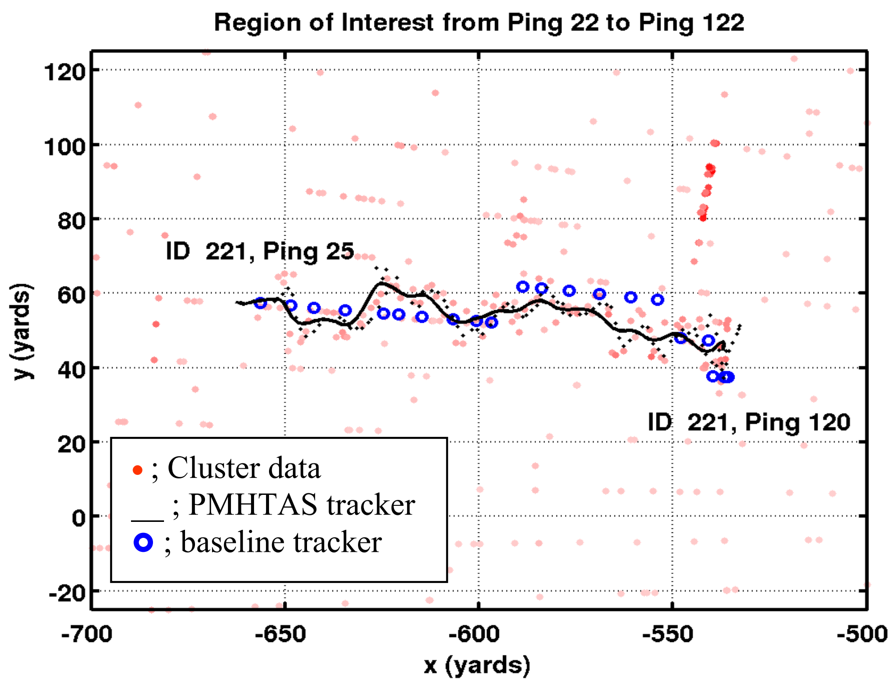

Figure 3. Subsurface Contact (configuration 1) run run 5A. Cluster data is shown in red, baseline tracker output is shown in blue and PMHTDAS track output is shown in black. Tracking performance is nearly identical for both systems on this data set.

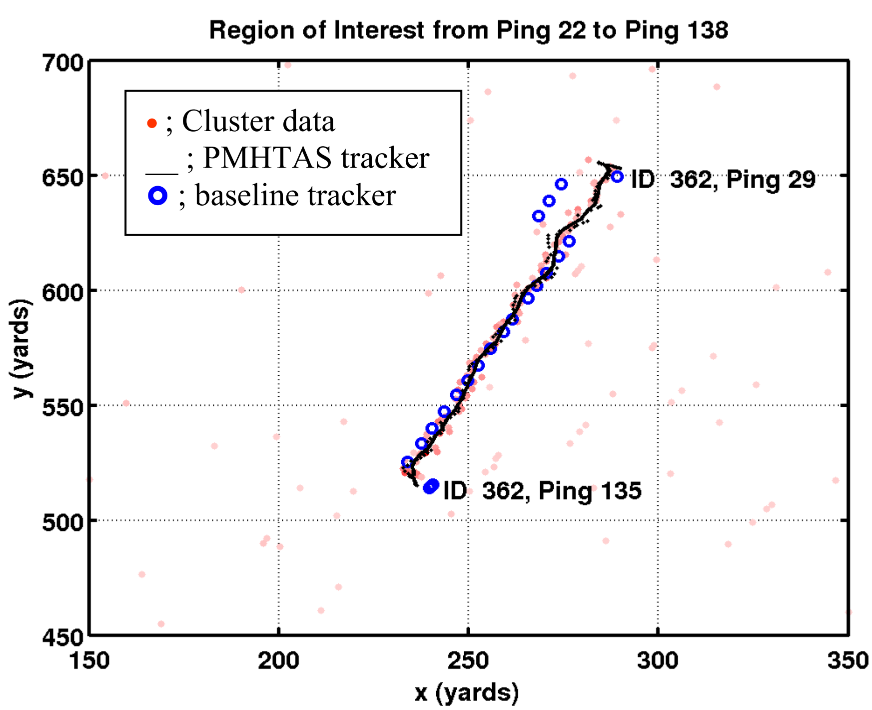

Figure 4. Subsurface Contact (configuration 1) run 10. Cluster data is shown in red, baseline tracker output is shown in blue and PMHTDAS track output is shown in black. Tracking performance is nearly identical for both systems on this data set.

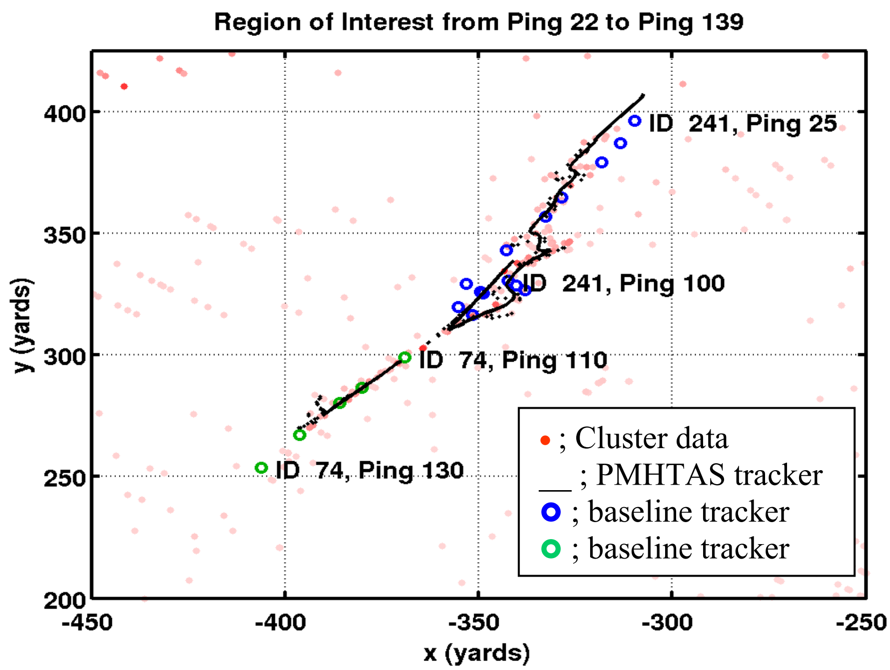

Figure 5. Subsurface Contact (configuration 1) run 14. Cluster data is shown in red, baseline tracker output is shown in blue and green, and PMHTDAS track output is shown in black. Tracking performance is nearly identical for both systems on this data set.

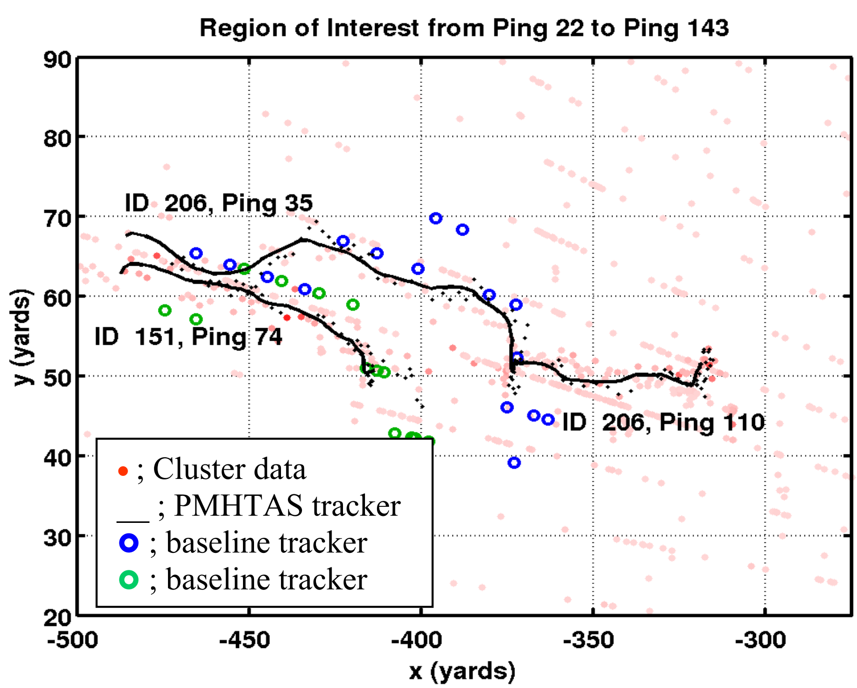

Figure 6. Subsurface Contact (configuration 2) run 2. Cluster data is shown in red, baseline tracker output is shown in blue and green, and PMHTDAS track output is shown in black. PMHTAS holds track on top contact substantially longer while baseline tracker holds contact on lower contact slightly longer.

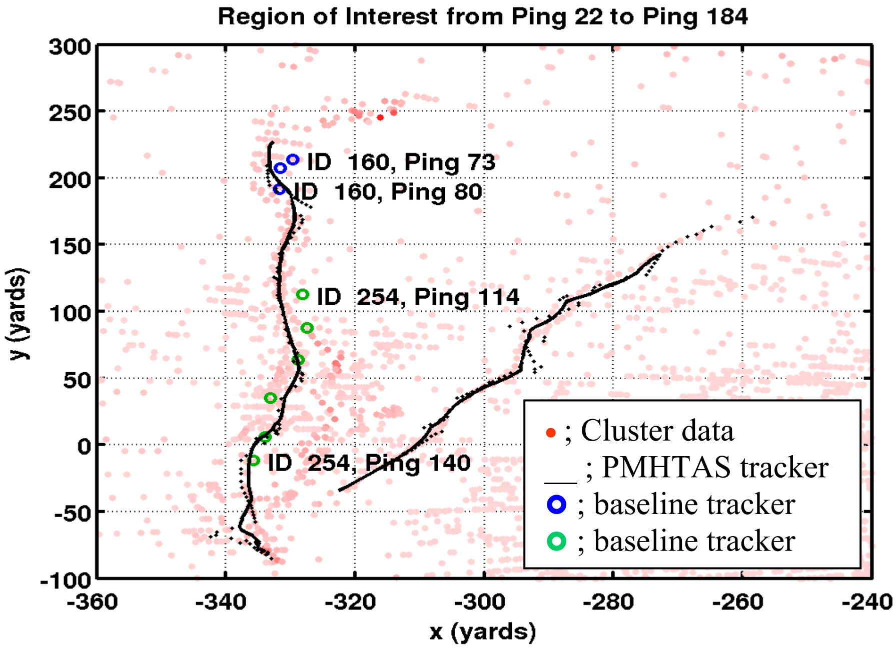

Figure 7. Subsurface Contact (configuration 2) run 5. Cluster data is shown in red, baseline tracker output is shown in blue and green, and PMHTDAS track output is shown in black. PMHTAS holds track continuously on both contacts for entire run while baseline tracker fragments the left target and fails to track the right target.

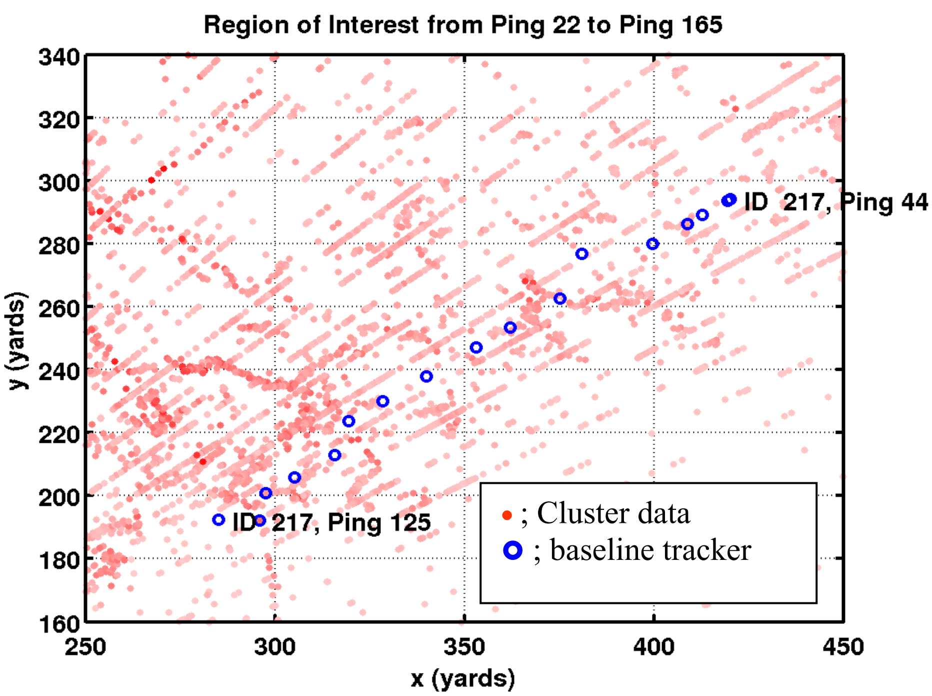

Figure 8. Subsurface Contact (configuration 2) run 10. Cluster data is shown in red, baseline tracker output is shown in blue. Baseline tracker tracks contact while PMHTAS fails to track.

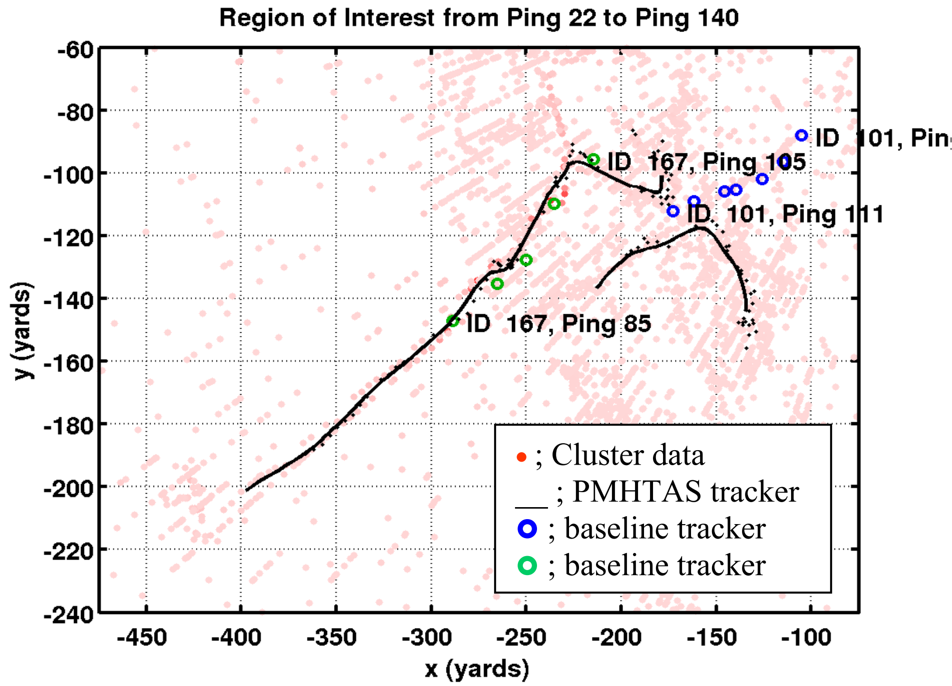

Figure 9. Subsurface Contact (configuration 2) run 13. Cluster data is shown in red, baseline tracker output is shown in blue and green, and PMHTDAS track output is shown in black. PMHTAS holds track much longer on left contact but is drawn off by clutter and loses track on the right contact.

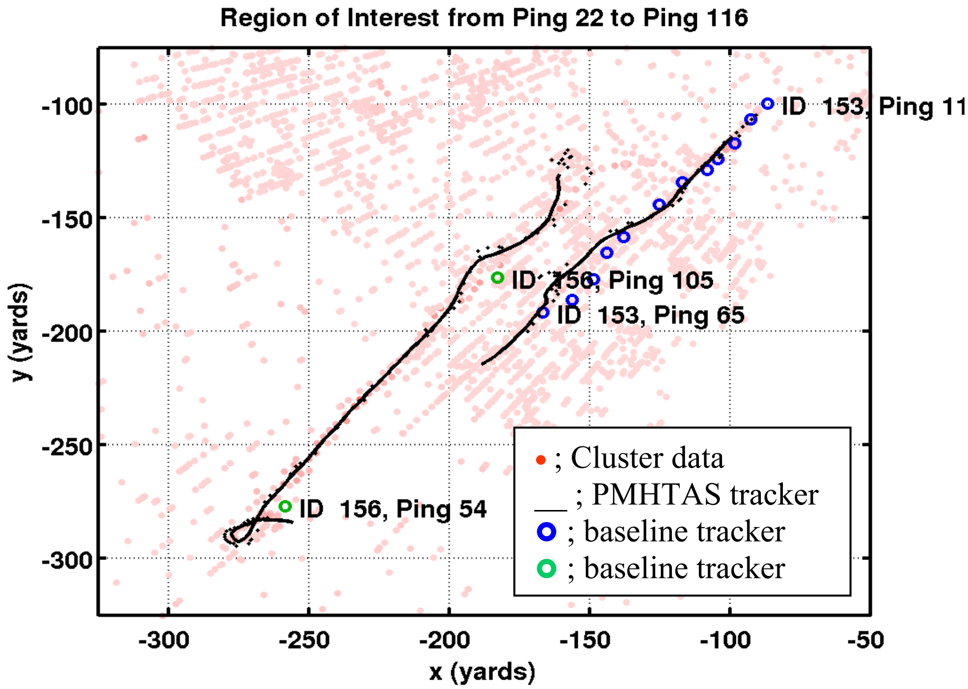

Figure 10. Subsurface Contact (configuration 2) run 14. Cluster data is shown in red, baseline tracker output is shown in blue and green, and PMHTDAS track output is shown in black. PMHTAS holds track much longer on left contact while baseline tracker holds track slightly longer on right contact.

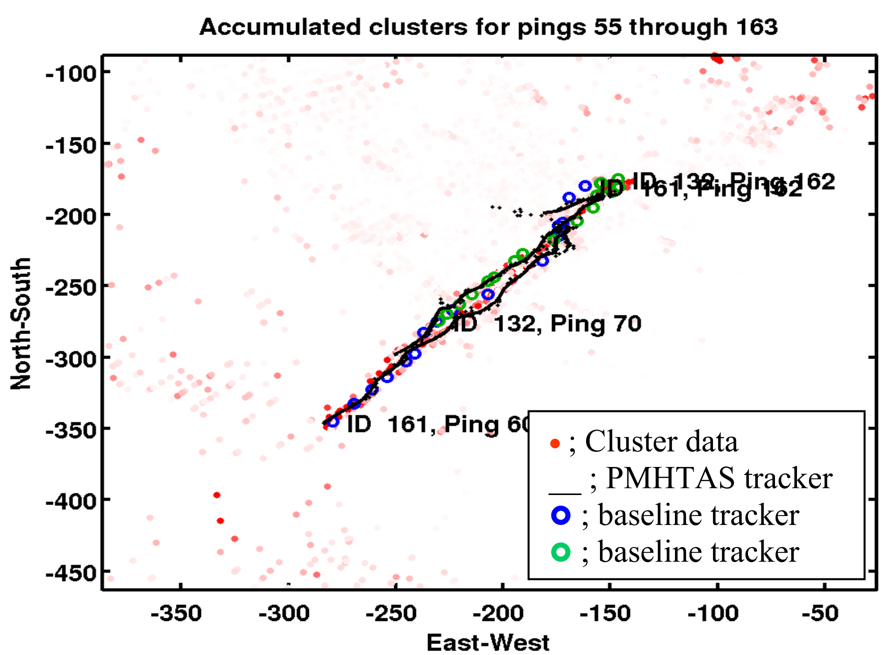

Figure 11. Surface contact run 2. Cluster data is shown in red, baseline tracker output is shown in blue and green, and PMHTDAS track output is shown in black. Baseline tracker and PMHTAS tracker achieve nearly identical performance on both contacts.

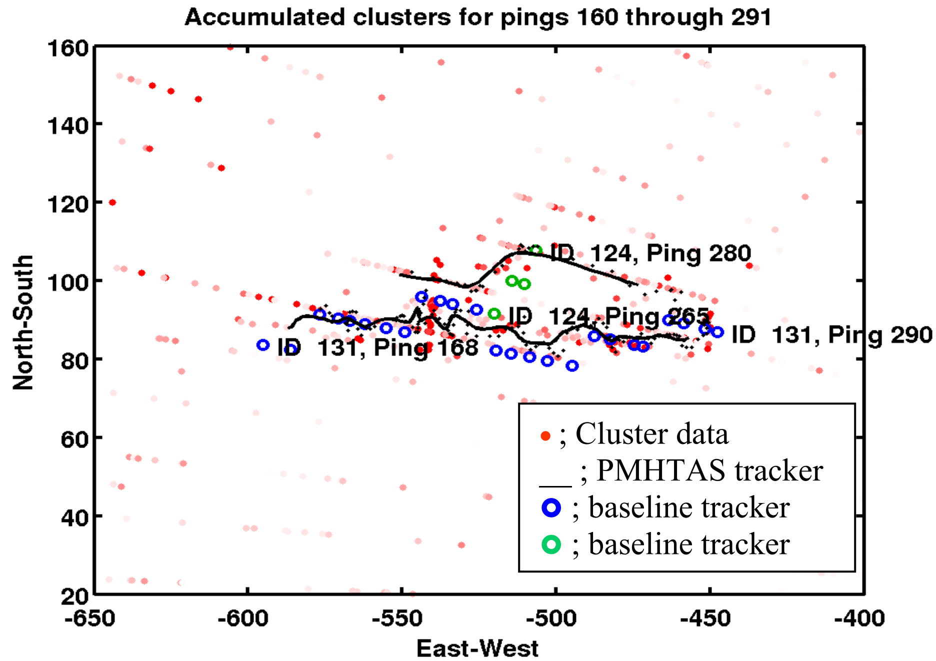

Figure 12. Surface contact run 5. Cluster data is shown in red, baseline tracker output is shown in blue and green, and PMHTDAS track output is shown in black. Baseline tracker and PMHTAS track bottom contact continuously. PMHTAS holds track significantly longer on upper contact.

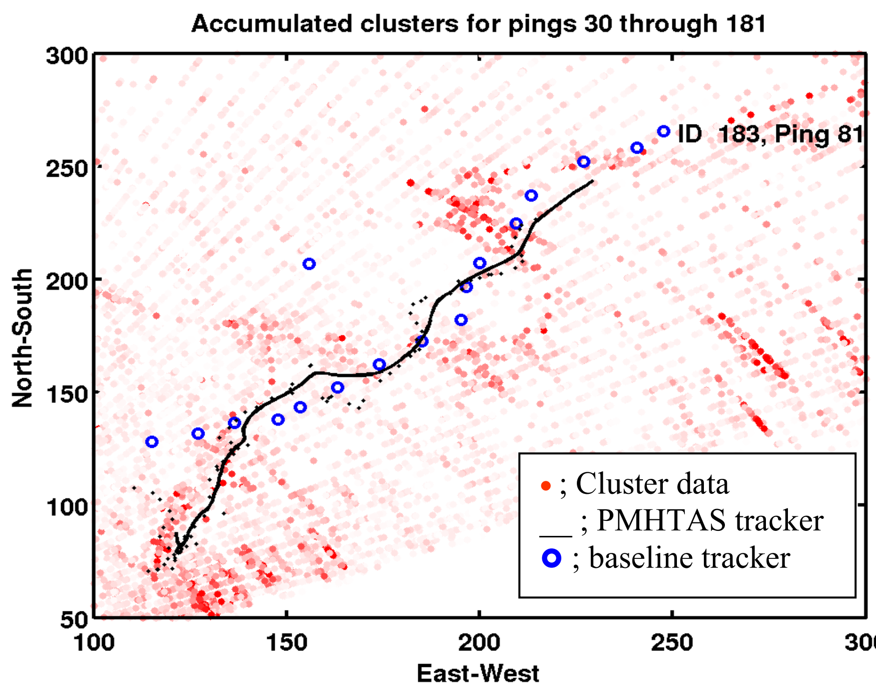

Figure 13. Surface contact run 11. Cluster data is shown in red, baseline tracker output is shown in blue and PMHTDAS track output is shown in black. Baseline tracker tracks contact earlier while PMHTAS holds track longer at end run.

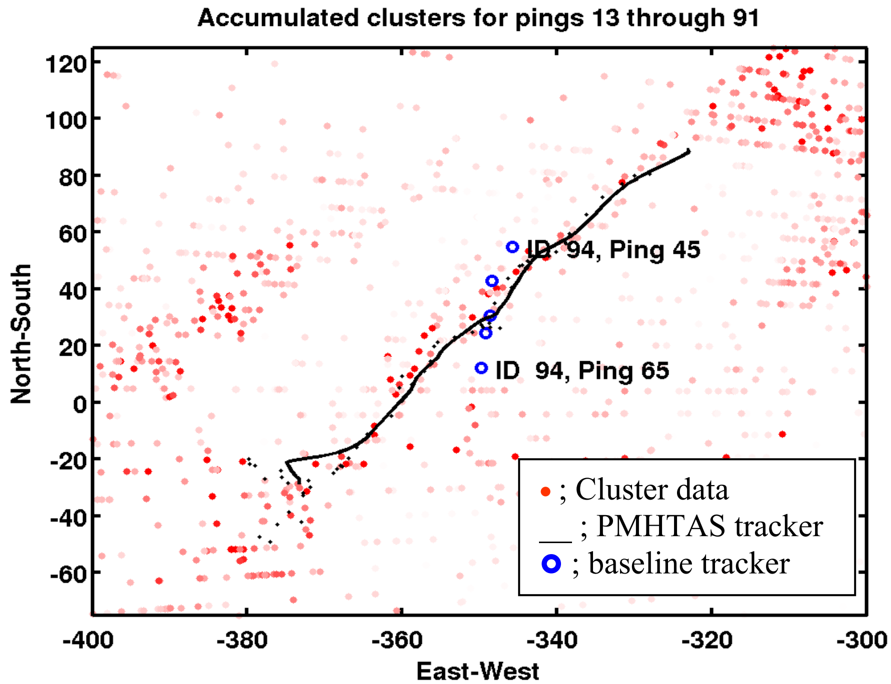

Figure 14. Surface contact run 13a. Cluster data is shown in red, baseline tracker output is shown in blue and PMHTDAS track output is shown in black. PMHTAS tracks contact for entire run while baseline tracker fails to track the contact at the beginning and end of run.

IMPACT/APPLICATIONS

With increased emphasis on the use of active sonar for port protection, demonstration of the value added by PMHTAS is expected to transition to appropriate fielded systems.

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